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Energy efficiency in China: measurement and policy

Jiang, Lei

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Chapter 4 Convergence of cross-province energy intensity in China

Abstract: This paper investigates convergence of cross-province energy intensity in China, based on a panel of 29 Chinese provinces for the period 2003-2012, by means of σ convergence, kernel density, unconditional and conditional β convergence. σ convergence analysis - based on the standard deviation - shows an overall downward trend throughout the sample period, implying σ convergence. Among the 10th, 25th, 50th, 75th, and 90th percentiles, the 90th exhibits the strongest decline, indicating that high energy intensive provinces reduce energy intensity more than low energy intensive provinces. The estimated kernel density function shows that annual average energy intensity gradually declines over time and that its distribution grows more compact and steeper, also indicating convergence. A spatial Durbin error model is applied to investigate both unconditional and conditional β convergence. We find evidence of unconditional β convergence. Conditional β convergence is divided into two types: one controlling for the fixed effects only, the other also for key exogenous variables and their spatial lags. We find that the conditional β convergence parameter obtained from the latter model is larger than that of the former, indicating that controlling for the key exogenous variables and their spatial lags tends to remove downward bias of the convergence parameter. We furthermore find that provincial gross product per capita, and the capital labor ratio in the own province and in neighboring provinces have negative impacts on the growth of energy intensity while the share of the secondary sector and investment in real estate and infrastructure in the own province and in neighboring provinces have positive impacts. FDI has a significant negative spatial spillover effect on the growth of energy intensity. From the analysis it follows that to reduce energy intensity growth, policies should be developed that stimulate income growth and the inflow of FDI, increase the capital labor ratio, reduce the share of the secondary sector and investment in real estate and infrastructure and stimulate research and development.

Keywords: Energy intensity; σ convergence; Conditional β convergence; unconditional β convergence; Kernel density; Spatial Durbin error model; China

4.1 Introduction

Since China started its economic reforms in 1978, energy consumption has risen five-fold. In 2009 China became the biggest energy consumer in the world, surpassing the U.S. (IEA 2010). In 2012, China for the first time accounted for more than half of global coal consumption (BP, 2013). China's energy consumption is expected to substantially rise in the coming decades. Due to its tremendous demand for energy, China is facing two major challenges: energy scarcity and environmental degradation (Song et al., 2011; Zhao et al., 2011; Jiang and Lin, 2012; Lin and Ouyang, 2014; Yao and Chang, 2014).

China's rapid demand for inter alia oil has surpassed its oil production. As a result, it has to import large quantities of oil to meet domestic demand (Ma et al., 2009). In 1993, China became a net importer of oil. Since then it has been facing rapidly increasing oil shortages. Specifically, the share of China's imported oil increased from 6.6% in 1995 to nearly 70% in 2011. By 2012, China's imports of crude oil and oil products reached 354.3 million tons which turned it into the world's second largest oil importer, after the U.S. (BP, 2013). China is to further expand its oil imports in the decades to come, which will have a huge impact on the international oil market (Konan and Zhang, 2008).

China also lacks sufficient natural gas resources. The rapid demand for natural gas surpassed its domestic production in 2007. In 2013, it became the sixth largest natural gas importer in the world (BP, 2014). In 2013, China's imports of natural gas (pipeline plus liquefied natural gas imports) reached 51.85 billion cubic meters. To (partly) meet its future demand, China signed a gas contract with Russia in 2014 worth 400 billion U.S. dollars for the coming three decades.

At present China is coal-affluent and self-sufficient. According to BP (2014), its proved coal reserves are 114500 million tons, accounting for 12.8% of the world's total, after the U.S. (26.6%) and Russia (17.6%). However, the coal R/P ratio, i.e. the ratio of coal reserves to production, which reflects the length of the period that the

remaining coal reserves will last, if production continues at the current rate, is 31. This is far behind the world average of 113, indicating that China may also suffer from coal shortage after three decades.

Alternatives to fossil fuels, particularly, hydro, nuclear and wind power, only account for 9.4% at present and offer no relieve. To sum up, energy scarcity is increasingly posing a tremendous threat to China's national energy security and economic development (Shen et al., 2005; He et al., 2010; Zhang and Lahr, 2014).

Energy consumption, especially of coal, has led to extremely serious air pollution problems in China (Cole, 2006; Aldy, 2007, Oikonomou et al., 2009; He et al., 2010), notably CO₂ emissions (Liu and Li, 2011) and water pollution (Chow, 2008; Qi et al., 2014). The ever-growing amount of CO₂ is the dominant contributor to global warming (Panopoulou and Pantelidis, 2009; Zhang and Cheng, 2009; Zhou et al., 2013). In 2009, China became the largest carbon dioxide emitter in the world (Yuan et al., 2014). Another major pollutant is sulfur dioxide caused by coal combustion. It causes acid rain, which has affected about 30% of China's total land area (Chow, 2008). Furthermore, acid rain flow into the water system and pollutes surface water and groundwater. China has also been the country with the highest emissions of nitrogen oxides (NO_x), ozone (O₃), sulfur oxide (SO_x) and particulates (PM) (Lin et al., 2010; Wang and Hao, 2012; Zhang et al., 2012). Chen et al. (2013) points out that air pollution has reduced life expectancy in large parts of China while Matus et al. (2012) describes some aspects of the burden of air pollution on China's economy.

Energy intensity is commonly defined as the ratio of energy consumption to GDP (Hang and Tu, 2007; Metcalf, 2008; Liddle, 2010; Stern and Jotzo, 2010). It measures the direct link between energy consumption and economic activity (Le Pen and Sévi, 2010). Energy intensity reduction means reduction of energy consumption, holding economic output constant. Hence, energy efficiency improvement has played a crucial role in addressing both the rapidly increasing energy scarcity and environmental degradation in China (Tanaka, 2008; Andrews-Speed, 2009). In concert with its rapid

increase in economic growth, China's energy intensity has decreased from 5.28 SCE (standard coal equivalent) per unit of GDP in 1990 to 2.25 SCE in 2012. However, the overall energy intensity still lags behind that of developed countries, such as the U.S. and Germany, and, notably, Japan. It is still 2.5 times higher than that of the world average (IEA, 2011), which implies that China has a huge potential to reduce its overall energy intensity with global implications for the demand for energy and energy-related emissions.

China's central government has long been aware of the need to improve energy efficiency (Lewis, 2010; Herrerias et al., 2013; Yuan et al., 2014). In its 11th Five-Year Plan (2006-2010), the central government included an imperative target of reducing overall energy intensity by 20% relative to the benchmark of 2005. Since there are substantial regional differences in energy resource endowments, economic growth patterns, and levels of technological development, energy intensity strongly varies across Chinese provinces. In general, the eastern provinces are the most efficient followed by the central and the western provinces. Therefore, the 11th Five-Year Plan specified targets for each province according to its specific level of technological development, industrial structure, and economic growth pattern. Accordingly, more stringent targets were set for the eastern provinces than for the western provinces with the central provinces taking an intermediate position. For example, the eastern provinces Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, and Zhejiang were required to reduce energy intensity by 20% whereas the targets for the western provinces Guangxi, Yunnan, Tibet and Qinghai were 15%, 17%, and 12%, respectively. However, the western provinces Sichuan and Chongqing were assigned the same targets as the eastern provinces because of their higher level of economic development. Furthermore, Jilin and Heilongjiang with large heavy industries were required to improve their energy efficiency by 30% and 20%, respectively, while the targets for the energy-rich (western) provinces Inner Mongolia, Shanxi, Guizhou and Shaanxi, were 25%, 25%, 20%, and 20%, respectively. See Table 4.1 for more details. The 11th Five-Year Plan was rather successful. By the end of 2010, China had

successfully reduced its overall energy intensity by 19.1%¹⁶.

In the 12th Five-Year Plan (2011-2015), the overall energy intensity target was a reduction of 16% from the 2010 benchmark. Furthermore, for each province a specific target was set. See Table 4.1 for details.

Table 4.1 Energy intensity reduction target (%) per province in the 11th and 12th Five-Year Plan

Eastern provinces			Central provinces			Western Provinces		
Province	11 th	12 th	Province	11 th	12 th	Province	11 th	12 th
Beijing	20	17	Shanxi	25	16	Inner Mongolia	25	15
Tianjin	20	18	Jilin	30	16	Guangxi	15	15
Hebei	20	17	Heilongjiang	20	16	Chongqing	20	16
Liaoning	20	17	Anhui	20	16	Sichuan	20	16
Shanghai	20	18	Jiangxi	20	16	Guizhou	20	15
Jiangsu	20	18	Henan	20	16	Yunnan	17	15
Zhejiang	20	18	Hubei	20	16	Tibet	12	10
Fujian	16	16	Hunan	20	16	Shaanxi	20	16
Shandong	22	17				Gansu	20	15
Guangdong	16	18				Qinghai	17	10
Hainan	12	10				Ningxia	20	15
						Xinjiang	20	10

Sources: http://www.sdpc.gov.cn/fzgggz/fzgh/zcfg/200611/t20061106_91998.html

http://www.gov.cn/gongbao/content/2011/content_1947196.htm

Although there still are substantial gaps among the provinces in terms of energy intensity, the question arises as to whether there is convergence among them. This question is the main research objective of this paper. The question is policy relevant in that confirmation of convergence indicates that the policies that have been used so far have been effective, and thus can be continued or reinforced.

Convergence is a concept that stems from the economic growth literature, particularly income growth (see Barro, 1991; Barro and Sala-i-Martin, 1991). The assumption behind convergence of per capita income is the diminishing returns of capital accumulation, implying that the initial differences in per capita income and capital endowment will vanish in the long term (Solow, 1956; Swan, 1956).

¹⁶ Source: http://zfs.mep.gov.cn/fg/gwyw/201109/t20110927_217786.htm

The concept of convergence has also been applied in energy intensity studies, mostly at country level. Mulder and De Groot (2007) show that technological progress, knowledge spillover, technology diffusion, and sectoral shifts are important sources of energy intensity convergence. They furthermore argue that technological progress may occur in two ways, viz. indigenous innovation and technology transfer. In the latter case, it is technology spillovers that make energy intensive countries or regions catch up with more advanced. Miketa and Mulder (2005) analyzed energy productivity (the opposite of energy intensity) convergence in 10 manufacturing sectors across 56 developed and developing countries for the period 1971-1995. They found evidence of convergence driven by energy prices and investment ratios (the share of investment to output), to a very limited extent though. Markandya et al. (2006) investigated convergence of energy intensity based on panel data for 12 Eastern European countries in transition and 15 European Union countries. They found evidence of convergence towards the European Union average. Additionally, the results showed that a 1% decrease in per capita income gap between transition countries and developed countries led to decline in the energy intensity growth rate of transition countries by 1.02%. Mulder and De Groot (2007) investigated convergence of cross-country energy productivity at sectoral level using a panel data of 14 OECD countries for the period of 1970-1997. They found convergence in terms of energy productivity partly because lagging countries benefited from the experience and technologies developed by advanced countries. Additionally, they also found that energy prices, investment, openness and specialization played a role in explaining the cross-country convergence. Herrerias (2012) investigated convergence of energy intensity for 83 countries, including developed and developing countries, over the period 1971-2008 by means of the distribution dynamics approach (see section 4.2.1 for a definition). She found a bimodal distribution for the developed countries, implying that energy policies had been successful in reducing energy intensity for the low energy intensity group, while further efforts should be developed for the high energy intensity group. The distribution for developing countries was found to be multimodal with a tendency towards a high level of energy intensity, implying that

developing countries were urgently needed to promote active energy policies to reduce their energy intensity.

Similar to international spillovers, regional spillovers may lead to regional convergence of energy intensity (Herrerias, 2011). There are few studies relating to the Chinese provinces in the international literature. An exception is Herrerias and Liu (2013), who investigated electricity intensity convergence across the Chinese provinces based on monthly data from January 2003 to December 2009 by means of a battery of unit root tests. They found that the majority of the Chinese provinces showed evidence of convergence. Another Chinese study is Qi and Luo (2007), who found evidence of convergence in the eastern and in the western provinces based on a panel of 30 provinces for the period 1995-2002. Another study was conducted by Yang and Fang (2008), based on a panel of 30 provinces for the period 1986-2006. They also found evidence of convergence.

A shortcoming of the international and regional studies of energy intensity convergence is that they do not explicitly model spatial spillover effects. This is an omission because, as observed above, a major vehicle of energy intensity convergence is technology diffusion across provinces or countries. Moreover, explicit inclusion of the technology spillover vehicles in a convergence model is not only needed from a substantive point of view but also from an econometric point of view, i.e. reduction of under-specification (Folmer and Oud, 2008). The present paper explicitly models the spillover drivers.

The paper is organized as follows. Section 4.2 introduces various concepts of convergence and their modeling approaches. Section 4.3 presents the empirical results and section 4.4 concludes.

4.2 Methods and conceptual model

The following two convergence concepts will be analyzed in this paper, viz. σ and β

convergence (Pettersson et al., 2013) ¹⁷.

4.2.1 σ convergence and kernel density estimation

σ convergence is defined as the decline in dispersion across a group of units. It is measured as the standard deviation (sd) (Barro and Sala-i-Martin, 1992; Mulder and De Groot, 2007; Yang and Fang, 2008). Specifically, let N denotes the number of provinces, ei_i energy intensity in province i , and \bar{ei} its mean. Then

$$sd = \sqrt{\frac{1}{N} \sum_{i=1}^N (ei_i - \bar{ei})^2} \quad (4.1)$$

A more general approach is analysis of distribution dynamics. Quah (1993, 1996a,b) proposed non-parametric kernel density estimation which allows visualization of the distribution dynamics across units (Ezcurra, 2007). It has two main advantages. First, it allows studying the distribution as a whole. Secondly, it allows detailed forecasting of the long run distribution including convergence of σ (De Beer, 2000; Ezcurra, 2007). Hence, it has recently gained popularity in empirical studies of convergence of energy intensity (see. Ezcurra, 2007; Liddle, 2010; Herrerias, 2012).

Kernel density estimation was developed by Rosenblatt (1956) and Parzen (1962). Given a set of independent and identically distributed random variables X_1, \dots, X_n from a distribution with density function $f(x)$, the kernel density estimator reads:

$$f(x) = \frac{1}{Nh} \sum_{i=1}^N K\left(\frac{x - X_i}{h}\right) \quad (4.2)$$

where N is the number of observations, K the kernel weighting function that integrates to 1 and h is the bandwidth.

To estimate the kernel density of energy intensity below, we use the Epanechnikov kernel (Epanechnikov, 1969) and Silverman's bandwidth (Silverman,

¹⁷ Because of the small number of observations across time, we will not analyze stochastic convergence which requires panel unit root tests (see Le Pen and Sévi, 2010).

1986). The estimated kernel density is quite robust to the chosen kernel function (e.g. Epanechnikov or Gaussian) (Marron and Nolan, 1988). We apply the Epanechnikov function because it has been extensively used in applied work (see Van, 2005; Azomahou, 2006; Aldy, 2007; Liddle, 2010). It reads:

$$K = \frac{3}{4}(1-u^2) \text{ if } |u| \leq 1, \text{ and } 0 \text{ otherwise} \quad (4.3)$$

where u is the argument of the kernel function.

The bandwidth h is more important to density estimation than the kernel function since it controls the smoothness (Silverman, 1986; Chiu, 1991; Chen, 1999; Wasserman, 2006). If too small bandwidths are used, very rough estimates result while over-smoothing results for too large bandwidths (Jones et al., 1996; Wasserman, 2006). A widely-used bandwidth was proposed by Silverman (1986). (See Van (2005), Aldy (2007), Liddle (2010) and Maza et al. (2010) for applications.) It reads:

$$h = 0.9\{\min(\sigma, \frac{IQR}{1.34})\}N^{-1/5} \quad (4.4)$$

where 0.9 is a coefficient, which is particularly suitable for multimodal densities (Sheather, 2004). IQR is the interquartile range, i.e. the difference, between the 75th percentile (Q3) and the 25th percentile (Q1), viz. $IQR=Q3-Q1$.

4.2.2 β convergence

β convergence focuses on the negative relationship between the initial level of a variable (i.e. energy intensity) and its growth rate. A significant negative β indicates that provinces with high energy intensity catch up with provinces with lower energy intensity. By including key determinants of energy intensity into the relationship, β convergence analysis provides insight into both differences in energy intensity among the units of analysis (provinces in the sequel), and the driving forces behind convergence patterns. It thus provides information for policymaking (Miketa and Mulder, 2005).

Energy intensity may converge to a common steady state for all provinces or to

different steady states for different subsets of the provinces. For that purpose, the concept of β convergence is divided into two types: viz. unconditional convergence and conditional convergence. The former refers to all provinces converging to a common steady state whereas the latter refers to different subsets of the provinces converging to different steady states that are conditional upon province-specific characteristics.

(1) Unconditional convergence

We model unconditional β convergence by means of a spatial Durbin error model (SDEM) that takes growth as a function of the serially lagged variable and a spatially lagged error term to take into account, in which the error in a given unit may be affected by the errors in neighboring units (Elhorst, 2014)¹⁸. In terms of the SDEM, the unconditional energy intensity convergence model reads:

$$g_{it} = \alpha + \beta \ln e_{i,t-1} + \varepsilon_{it} \quad (4.5a)$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^N w_{ij} \varepsilon_{ijt} + v_{it} \quad (4.5b)$$

where g_{it} denotes the growth of energy intensity of province i at time t , $\ln e_{i,t-1}$ the natural logarithm of lagged energy intensity $e_{i,t-1}$ and α the constant term. The spatially correlated error term ε depends on the error term of the neighboring provinces and an idiosyncratic component v . Particularly, w_{ij} in (4.5b) is an element of the $N \times N$ spatial weights matrix W that captures the spatial structure of the Chinese provinces. We apply a binary first-order rook-contiguity spatial weights matrix, whose elements equal 1 if two provinces share a common border, and 0 otherwise. λ is the spatial autocorrelation coefficient. The sign of β indicates β convergence. If β is negative and significant, there is significant β convergence.

¹⁸ We opt for a spatial Durbin error model rather than the more general spatial Durbin model which includes a spatially lagged dependent model because there are no theoretical grounds that the growth of energy intensity in one province directly affects the growth of energy intensity in other provinces. The spatial Durbin error model allows for spatial dependence among the errors and among the exogenous variables. For introductions to spatial econometrics, we refer to LeSage and Pace (2009), Elhorst (2014), Fisher and Wang (2011).

(2) Conditional convergence

As discussed above, conditional convergence allows different subsets of provinces to converge to different levels, depending on province-specific conditions. One way of modeling conditional convergence is by controlling for individual specific fixed effects and time period fixed effects, i.e. by applying the following fixed effects spatial Durbin error model:

$$g_{it} = \alpha + \beta \ln e_{it-1} + \mu_i + \gamma_t + \varepsilon_{it} \quad (4.6a)$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^N w_{ij} \varepsilon_{ijt} + v_{it} \quad (4.6b)$$

where μ_i and γ_t represent the spatial fixed effects and time period fixed effects, respectively.¹⁹ All other variables are the same as in equation (4.5).

An alternative, more informative, and more adequate, approach is to add controls and their spatial spillover vehicles to model (4.6). For this purpose, we apply the general spatial Durbin error model:

$$g_{it} = \alpha + \beta \ln e_{it-1} + x_{it} \theta + \sum_{j=1}^N w_{ij} x_{ijt} \delta + \mu_i + \gamma_t + \varepsilon_{it} \quad (4.7a)$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^N w_{ij} \varepsilon_{ijt} + v_{it} \quad (4.7b)$$

where x_{it} is a $1 \times K$ row vector of exogenous variables in logs and θ a $K \times 1$ column vector of coefficients. In a similar vein, the $1 \times K$ row vector x_{ijt} with $K \times 1$ column vector of coefficients δ contains the controls in neighboring provinces that affect growth g_{it} . All other variables are the same as in equation (4.5) and (4.6).

Note that equation (4.7a) explicitly models spatial spillover effects of the controls, i.e. the mechanisms in neighboring provinces that affect energy intensity convergence

¹⁹ We consider the random effects model unlikely because of the substantial structural differences among the Chinese provinces which make it highly unlikely that the observations are random draws from a large population (Islam, 2003). Nevertheless, we will test the fixed effects model versus the random effects model below.

in a given province. The model allows investigating whether spatial spillover effects can speed up convergence.

(3) Explanatory variables of conditional convergence

Based on a literature review, we now discuss the controls in (4.7a) which include Gross Provincial Product per capita (*GPPc*), the share of the secondary sector (*Secondsec*), investment in real estate and infrastructure (*Invest*), capital labor ratio (*Clratio*), foreign direct investment (*FDI*), and energy reserves (*Enres*). The variables, their definitions, measurements and expected signs are presented in Table 4.2.

GPPc. The impact of this variable on energy intensity development is ambiguous. On one hand, more income leads to more consumption and investment which, at an early stage of development, may increase energy intensity (the upward sloping section of the environmental Kuznets curve (Grossman and Krueger, 1993; Cole and Rayner, 2000; Antweiler et al., 2001)). On the other hand, as income rises, citizens become environmentally aware and demand protection via environmental regulation (the downward sloping part of the environmental Kuznets curve (Suri and Chapman, 1998; Dinda, 2004; Song and Zheng, 2012)). Besides, rising income tends to push the economic structure towards lower energy intensive industries (Suri and Chapman, 1998) and induces environment-related research and development, and more advanced, energy efficient technology adoption (Komen et al., 1997). Hence, under these conditions *GPPc* has a negative impact on energy intensity growth.

Secondsec. The secondary sector is the largest energy consumer in China. For example, it accounted for 65.2% of total energy consumption in 2012, but merely produced 45.3% of China's GDP. Although the share of the secondary sector has gradually declined in recent years, it's still higher than the share of the tertiary industry. The larger its share of the secondary sector, the more energy intensive a province is, *ceteris paribus*. Hence, we expect *Secondsec* to have a positive impact on energy intensity growth.

FDI. Foreign direct investment is a major vehicle for developing countries to

acquire advanced technologies and knowledge from developed countries. It thus is expected to have a negative impact on energy intensity growth (Fisher-Vande et al., 2006; Hang and Tu, 2007; Mulder and De Groot, 2007; Hubler and Keller, 2010). Zheng et al. (2011) and Herrerias et al. (2013) show that the large quantities of FDI flowing into China have reduced its overall energy intensity. We hypothesize that *FDI* has a negative impact on the growth of energy intensity.

Invest. In recent years, the Chinese central government has stimulated its economy by means of large scale investments in real estate and infrastructure. Accordingly, substantial deals of energy-intensive products, such as cement and steel, were consumed (Guo et al., 2009). We expect *Invest* to have a positive impact on energy intensity growth.

Clratio. The capital-labor ratio can be used as a proxy for the vintage of capital (Metcalf, 2008; Wu, 2012). A low *Clratio* indicates old-fashioned technology with high energy intensity. We hypothesize that *Clratio* has a negative effect on the growth of energy intensity.

Enres. Energy intensity is closely related to energy resource endowment. Particularly, energy-rich provinces tend to develop energy-intensive industries because of easy access to energy resources. On the other hand, the ever-growing energy scarcity induces energy-short provinces to seek ways to reduce energy intensity in China (Wang and Zhong, 2009; Song and Zheng, 2012). Hence, we hypothesize that *Enres* has a positive effect on the growth of energy intensity.

Spatial spillover effects (W) As noted above, spatial spillover effects are important drivers of convergence of energy intensity. For example, via input-output relationships rising income in one province may stimulate per capita income in neighboring provinces and thus stimulate energy intensity or, the opposite, dampen energy intensity via the demand for environmental quality and environmental protection. *Secondsec* in one province may also have an impact on energy intensity in neighboring provinces via interprovincial intra-sector input-output linkages. As

described above, cross-province convergence of energy intensity is *inter alia* affected by knowledge spillover. This applies also to FDI. It may work in three ways, viz. via a demonstration effect, labor turnover and vertical linkage i.e. the links between foreign firms in the own province and local suppliers in neighboring provinces (Hu and Jefferson, 2002; Cheung and Lin, 2004). New technologies and knowledge may be embedded in advanced capital, proxied by *Clratio*. There will be spatial spillover with a dampening effect on energy intensity when advanced capital flows from advanced provinces into lagging provinces. A positive spatial spillover effect on energy intensity growth may result from investment in real estate and infrastructure, if this kind of investment in one province boosts similar investments in neighboring provinces. *Enres* may have a positive spatial spillover effect when an energy-short province imports energy or energy resources from energy-rich neighboring provinces at a low price. Spatial lags are denoted by $W*variable\ name$. They are measured in the same units as the own variables and are expected to have the same signs.

Table 4.2 The variables, their definitions, measurements and expected signs of the coefficients

Variable	Definition	Unit	Expected sign
g	The natural logarithm of the ratio of energy intensity to 1-year lagged energy intensity		
ei	The ratio of energy consumption to <i>GDP</i>	Ton/10,000 Yuan	-/+
$GPPc$	<i>GPP</i> Per capita	10,000 Yuan/capita	-/+
$Secondsec$	The share of the secondary sector in <i>GPP</i>	%	+
$Invest$	The share of investment to <i>GPP</i>	%	+
$Clratio$	The ratio of capital to labor	10,000 Yuan/capita	-
FDI	The ratio of FDI to <i>GPP</i>	%	-
$Enres$	Energy reserves per capita	Ton/capita	+

Note: A negative sign indicates convergence.

Sources: China Energy Statistical Yearbook (2004-2013), China Statistical Yearbook (2004-2013), China Industry Economy Statistical Yearbook (2004-2013) and China Economic Database (CEIC)

4.3 Empirical results

As a preliminary step to the empirical analysis below, we present descriptive statistics (means, standard deviations (sd), min and max values) in Table 4.3.

Table 4.3 Descriptive statistics

Variable	Mean	SD	Min	Max
<i>g</i>	-0.03	0.04	-0.17	0.19
<i>ei</i>	1.68	0.83	0.59	4.51
<i>GPPc</i>	1.93	1.29	0.37	6.65
<i>Secondsec</i>	47.75	6.82	23.09	59.05
<i>Invest</i>	54.67	12.41	31.17	88.18
<i>Clratio</i>	7.49	5.48	1.06	31.34
<i>FDI</i>	2.73	2.16	0.09	10.51
<i>Enres</i>	266.67	545.89	0.16	2398.72

Sources: See Table 4.2.

For definitions of the variables, see Table 4.2.

4.3.1 σ convergence and kernel density

We first test σ convergence by means of the development of standard deviation of energy intensity in levels. The result is presented in Figure 4.1.

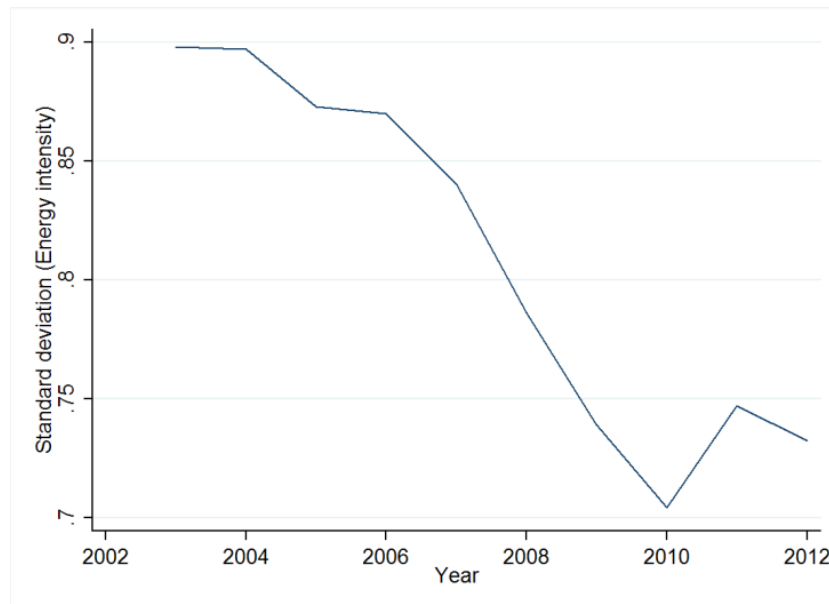


Figure 4.1 Standard deviation of energy intensity, 2003-2012

Figure 4.1 shows an obvious overall downward trend in the dispersion of energy intensity over the period 2003-2012. The annual standard deviation of energy

intensity went down from 0.8982 in 2003 to 0.7043 in 2010. From 2010-2011, however, there was an increase, immediately followed by a downward movement. From Figure 4.1 it follows that during the period 2003-2010 the energy intensity gap across the Chinese provinces narrowed, as stipulated in the 11th Five-Year Plan for the period (2006-2010). The upsurge at the beginning of the 12th Five-Year Plan (2011) is probably due to the fact that the energy-rich provinces boosted economic growth to improve their political performance at the expense of energy intensity improvement. In the second half of 2011, each province's specific energy policy targets including energy intensity reduction, as specified in the 12th Five-Year Plan, started being implemented so that the standard deviation started declining again. To conclude, Figure 4.1 supports σ convergence.

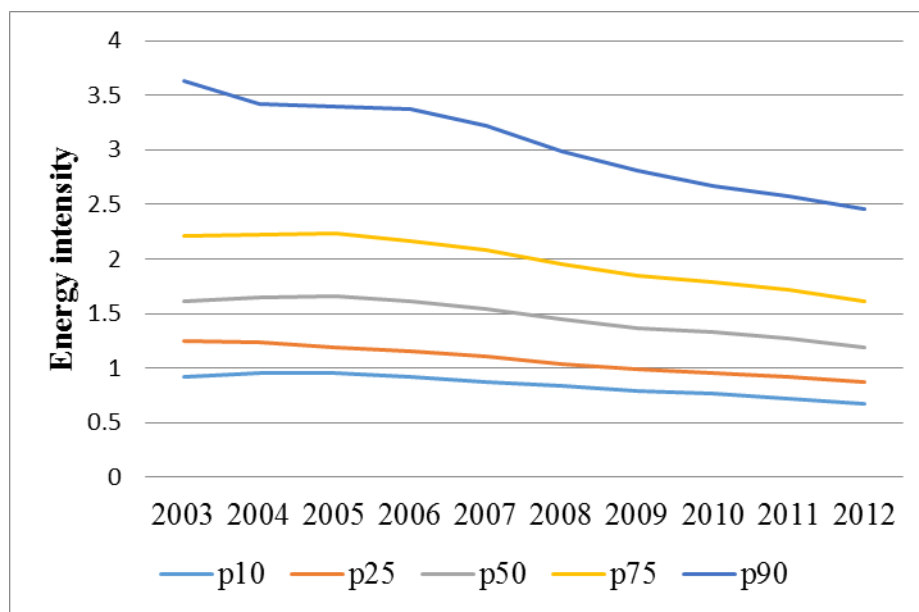


Figure 4.2a Energy intensity dynamics of the 10th, 25th, 50th, 75th, and 90th percentile

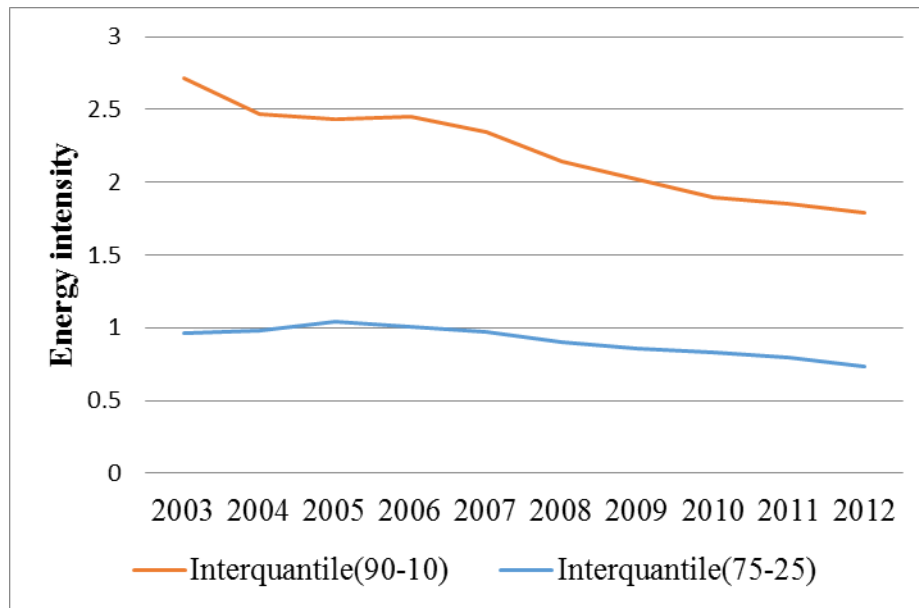


Figure 4.2b Energy intensity dynamics of the 90-10 and 75-25 IQRs

Figure 4.2a presents the dynamics of the 10th, 25th, 50th, 75th, and 90th percentiles of energy intensity for the period 2003-2012. All of them show downward trends. Among them, the 90th percentile shows the strongest decline and the 10th and 25th percentile the least, indicating that high energy intensive provinces reduced energy intensity more than the low energy intensive provinces.

Figure 4.2b presents the dynamics of IQR (90-10) and IQR (75-25). The former decreased over the entire period from 2.7123 in 2003 to 1.7864 in 2012, except between 2004 and 2007 when it was constant. IQR (75-25) shows a different development. It slightly increased from 0.9632 in 2003 to 1.0429 in 2005 before declining to 0.7384 in 2012. The different developments of the two IQRs reflect the differences in energy policy by China's central government. Before 2005, it had implemented no energy intensity reduction policy. Consequently, the energy intensity gap changed unstably between provinces with high energy intensity and those with low energy intensity. Because of the introduction of energy intensity targets for each province in 2006, the gap stably narrowed. To conclude, the energy policy did not only reduce overall energy intensity, but also narrowed the energy intensity gap.

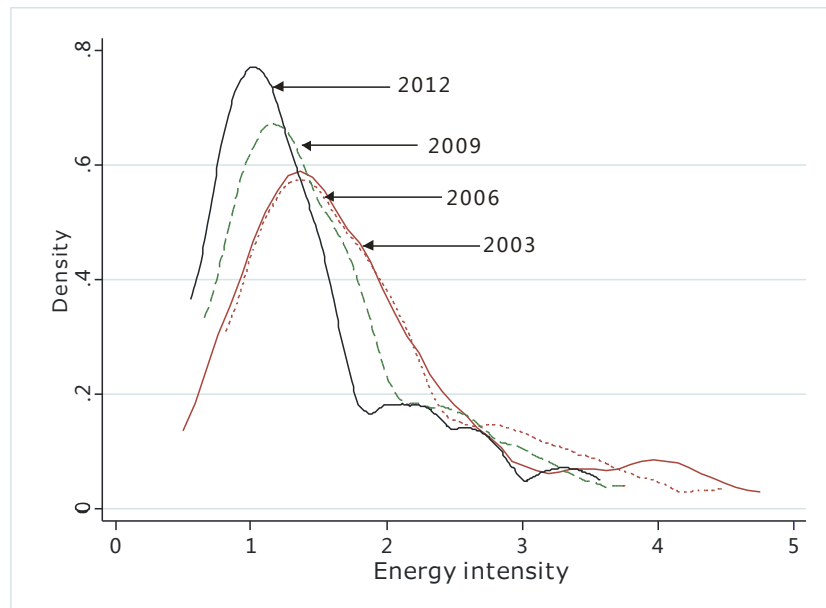


Figure 4.3 Estimated kernel density for energy intensity, 2003, 2006, 2009, 2012²⁰

Figure 4.3 displays the estimated kernel density distributions for 2003, 2006, 2009, and 2012. The figure shows that the distributions of cross-province energy intensity become more compact and steeper, indicating convergence. Particularly, the peak of the distribution gradually moves to the left, and simultaneously increases from 2003 to 2012, implying that annual average energy intensity declines over time and that there is convergence. The upper tail of the distributions decreased over time, implying that provinces with high energy intensity have improved.

4.3.2 β convergence

In this subsection we empirically analyze β convergence of energy intensity among Chinese provinces. We first consider unconditional convergence, next two types of conditional convergence. The estimation results are presented in Table 4.4.

Table 4.4 Unconditional and conditional β convergence of energy intensity

Dependent variable	Energy intensity growth g			
	Model (5)	Model (6)	Initial Model (7)	Final Model (7)
Independent Variables				
$\ln EI_{t-1}(\beta)$	-0.0026 (-0.8638)	-0.1274(-9.2192)** *	-0.1616 (-11.0193)***	-0.1628 (-11.1502)***

²⁰ The distributions for the years not reported fit into the pattern displayed. They are available upon request from the first author.

<i>LnGPPc</i>			-0.1102 (-2.4690)**	-0.1082 (-2.4221)**
<i>LnSecondsec</i>			0.0689 (1.8961)**	0.0714 (1.9829)**
<i>LnFDI</i>			-0.0036 (-0.8078)	-0.0032 (-0.7390)
<i>LnEnres</i>			0.0070 (0.8544)	
<i>LnClratio</i>			-0.0472 (-2.2481)**	-0.0473 (-2.2562)**
<i>LnInvest</i>			0.0831 (3.4640)***	0.0815 (3.4008)***
<i>W*LnGPPc</i>			-0.1780 (-1.8022)*	-0.1744 (-1.7648)*
<i>W*LnSecondsec</i>			0.2341 (2.9739)***	0.2321 (3.0041)***
<i>W*LnFDI</i>			-0.0368 (-3.5917)***	-0.0371 (-3.6261)***
<i>W*LnEnres</i>			-0.0043 (-0.2248)	
<i>W*LnClratio</i>			-0.0922 (-2.2441)**	-0.0947 (-2.3034)**
<i>W*LnInvest</i>			0.1403 (2.6698)***	0.1403 (2.6771)***
Constant	-0.0253 (-3.6645)***	0.1846 (7.8939)***	1.2307 (1.2256)	1.1957 (1.1929)
<i>lambda</i>	0.5340 (8.8509)***	0.2692 (3.4693)***	0.1631 (1.9852)**	0.1651 (2.0118)**
Spatial fixed effects		147.6917***	151.4013***	159.3114***
Time fixed effects		223.8604***	42.3556***	45.4635***
Adjusted-R ²	0.0062	0.2408	0.3967	0.3945
Log-likelihood	496.7763	601.0715	629.3887	628.9478

Note: t statistics in parenthesis. * :p<.10, ** :p<.05, *** :p<.01.

Definitions of the variables under Table 4.2.

W* denotes the spatially lagged variable. $W_{ij} = 1$ if two provinces share a common border, 0 otherwise; $W_{ii}=0$

The second column in Table 4.4 presents the unconditional convergence results, based on model (4.5). The coefficient β is negative, though insignificant. The insignificance is probably due to the fact that there are large differences across the provinces in terms of inter alia economic structure, energy resource endowment, and level of technological development. As shown by Liddle (2009), a prerequisite for convergence is that the provinces have similar economic structures. In the case of different economic structures, they will tend to grow toward their own steady states. In other words, the estimated model (4.5) points to conditional convergence analysis.

The third column in Table 4.4 shows the estimated conditional convergence model with two-way fixed effects. (Since the spatial and time-period fixed effects per se are not interesting, they are not presented here; they are available upon request from the first author.) We tested the null hypothesis that the spatial fixed effects are

jointly insignificant by means of the likelihood ratio test. The Chi square value was 147.6917 with 29 degrees of freedom, $p < 0.01$, leading to the rejection of the hypothesis that the spatial fixed effects are jointly insignificant at 1% significance level. In a similar vein, the hypothesis that the time-period fixed effects are jointly insignificant was rejected at 1% significance level (Chi square value 223.8604 with 9 degrees of freedom, $p < 0.01$). Both outcomes justify controlling for the spatial and time-period fixed effects. Besides, a Hausman test of a fixed effects versus a random effects model rejected the latter, as expected. The coefficient β of -0.1274 is significant and negative, indicating conditional convergence.

The fourth column in Table 4.4 presents the estimated conditional model with all the “own” variables and their spatial lags. We applied a stepwise backward elimination procedure to the Initial model (4.7). $LnEnres$ and $W*LnEnres$ turned out to be highly insignificant in the Initial model and were deleted. A possible explanation for the insignificance of $LnEnres$ and $W*LnEnres$ is that there is very little variation in energy reserves over time. The outcome of the backward elimination procedure is the Final model (the fifth column in Table 4.4) which we will discuss next.

The significant and negative coefficient β of -0.1628 in the fifth column is larger (in absolute value) than the value of -0.1274 in the third column, implying that controlling for the main determinants and their spatial spillovers removes downward bias of the estimator of the convergence parameter.

$LnGPPc$ has a significant, negative effect on the growth of energy intensity, indicating that rising income leads to a decline of energy intensity growth due to increased environmental awareness and investment in environment-related research and technological development. $W*LnGPPc$ is also significant and negative, indicating that rising per capita income in neighboring provinces, via spatial spillovers, reduces energy intensity growth in a province. As hypothesized in section 4.2.2, $Lnsecondsec$ has a positive and significant effect, indicating that the development of the secondary sector drives energy intensity growth up. $W*Lnsecondsec$ is also positive and significant, indicating the presence of growth stimulating effects from

neighboring provinces via inter-industrial input-output relationships. $LnFDI$ has a negative effect, though insignificant, indicating that “own” FDI does not significantly reduce energy intensity in a province. Curiously, $W*LnFDI$ has a significant and negative effect, indicating that there are significant growth dampening spatial spillover effects to neighboring provinces. A possible explanation is that most FDI is concentrated in coastal provinces with relatively low marginal impacts on energy intensity. In neighboring provinces with far less FDI spatial spillovers in the form of technology diffusion tend to dampen energy intensity growth. $LnClratio$ is negative and significant, indicating that more recent vintages lead to a decline in energy intensity growth. $W*LnClratio$ is also negative and significant, indicating that advanced technologies embedded in new capital in neighboring provinces diffuses to neighboring provinces, which contributes to the decline in energy intensity growth. $LnInvest$ is significant and positive, indicating that investment in real estate and infrastructure drives energy intensity growth up. $W*LnInvest$ is also significant and positive, indicating its growth stimulating spillover effects to neighboring provinces. The spatial autocorrelation coefficient λ is significant, indicating spatial dependence among the residuals.

4.4 Summary and conclusions

In this paper, we have analyzed convergence of cross-province energy intensity based on a panel data set of 29 Chinese provinces over the period 2003-2012 using the following approaches: σ convergence, kernel density, unconditional and conditional β convergence. The following conclusions have emerged from these analyses. First, the cross-province energy intensity gap has narrowed throughout the sample period, with a short, yet explainable, interruption in 2011, as indicated by the σ convergence analysis. This generic downward trend coincided with varied rates for provinces of different energy intensity levels, as suggested by the dynamics of various percentiles: energy intensity declined more rapidly in the high-level provinces than the others. Apparently, this situation has caused a narrowing effect to the overall energy intensity

gap among provinces, as indicated by the dynamics of IQRs. The narrowing might be attributed to the implementation of the nation's energy intensity reduction policies during the sample period. Convergence also follows from the results of the estimated kernel densities, which indicate a steepening and narrowing of the distribution of energy intensity over time. According to the β convergence model results, however, the revealed convergence among provinces is hardly unconditional, owing to their large disparity in economic structures. As a further verification of its conditional nature, convergence was tested using two types of models, viz. a model with two-way fixed effects only and a model also controlling for the systematic determinants and their spatial lags. While the first model revealed significant conditional convergence of energy intensity across provinces over time, the second model revealed even stronger conditional convergence, because bias of the estimator of β was reduced.

Cross-province energy intensity convergence may be evidence of a leapfrogging process (Mielnik and Goldemberg, 2000) which implies general diminishing technological differences across provinces over time (Herrerias, 2011). In addition to per capita income and more recent capital vintages, the spillover effects of large FDI inflows are responsible for boosting the level of technologies in a short period of time. This is especially true in China as it has, over the last two decades, been the biggest receptor of FDI among all developing countries (Elliott et al., 2013).

As the core of the Western Development Strategy Program, China's central government has since 2000 issued a series of preferential economic policies for underdeveloped western inland provinces to attract foreign investment. This effort has so far been fruitful: the aggregate FDI in western provinces accounted for 4.22% of China's total in 2000 to 14% in 2011, versus the fact that the share of the aggregate FDI in eastern provinces to China's total decreased from 86.71% to 67.38% over the same period. The nearly 10% increase in the west and 20% decline in the east suggest that to some extent technological differences were narrowed down between the two regions. Even so, the current cross-province technological gap still remains remarkable, and converging to a common steady state is unlikely to happen in the

short run, in spite of the favorable spillover effects. Hence, in the coming Five-Year Plan, more FDI inflow into the western provinces should be encouraged through more targeted economic policies in order to further narrow technological differences between the east and the west. In a broader context, future convergence between the two regions relies on further opening up of economic sectors for FDI inflows. Due to ownership issues, the current FDI inflows into such sectors as mining, construction, financial intermediation, and education are still highly restricted by the central government, indicated by their ratio of FDI to added value as being merely 0.14%, 0.18%, 0.49%, and 0.002%, respectively. The mining industry comprises a major part of the economies in many western provinces; apparently its technological advancement will help to bridge the technological gap and greatly improve cross-province convergence in energy intensity.

As the largest “World Factory”, China has long been locked into the secondary sector for its rapid economic development, which is a major contributor to its high level of energy intensity. In order to reduce overall energy intensity and reverse the environmental degradation trend, new clean technologies need to be developed as a nationwide priority and adopted in all industrial production processes. Besides, due to the rapid increase in energy costs, the wealthy eastern provinces should consider significant economic restructuring by transferring conventional industries (e.g. energy intensive steel industry) to high value-added industries (e.g. information industry). To retain the status of the world biggest manufacturing nation, the energy intensive industries can be induced to move from the eastern provinces to the energy-rich and low labor-cost western provinces. Apparently, the nationwide industry shift need be guided by the central government from a strategic perspective to avoid overconcentration of inter alia energy-intensive industries in certain energy-rich provinces.

One important policy handle for improving both overall energy intensity and cross-province convergence is the promotion of international and domestic technology diffusion. International technology transfers from advanced countries

were a common practice in the eastern coastal provinces at the early stage of the economic reforms. With locational advantages and improved basic infrastructures, these provinces were spearheads to attract foreign investment and advanced technologies for export-oriented production. This channel of acquiring new clean and energy-efficient technologies from overseas should be kept wide open, so that these provinces can act as an important technology base for internalizing the newest knowledge and development from advanced countries. A mechanism of absorption, digestion, and re-innovation must be established to secure the sustainability of this important technology diffusion channel. Domestic technology diffusion, on the other hand, focuses on indigenous technology transfer mainly from the coastal east to the inland west. Hence, policies (e.g. tax relief, land grant) for encouraging the coastal east to team up with the inland west need be designed and implemented, so that long-term interaction aimed at improving energy efficiency through technology transfer can be established. With relatively low labor and energy costs plus newly adopted efficient technology, the inland west will not only improve its ability to meet local market demand, but also enable itself to compete in the international market. This is in fact a win-win situation for both the coastal east and the inland west, especially when either region is characterized with a different industrial structure. That is, although the structure of production costs remains different, the overall production costs will converge more rapidly than the convergence of energy intensity alone. This will lead to a more equally based exchange of value-added products between the two regions and help to narrow down the gap of regional economic development.

Indigenous innovation is of most importance to develop domestic innovation capabilities. Only if China exhibits substantial domestic innovation capabilities, it may absorb international technology and knowledge more effectively and efficiently. International technology transfer and indigenous innovation transfer need interact to create spatial spillovers to reduce energy intensity. To sum up, in order to not only narrow the energy intensity gap across provinces, but also reduce the overall energy

intensity, policies aimed at facilitating technology diffusion through FDI and indigenous investment should be encouraged.

For political reasons, China has been suffering from restricted imports of advanced technologies and products (Zhan, 2006; Lopez-Casero, 2010). Due to trade barriers, some of the newest energy-efficient technologies are inaccessible to Chinese buyers in the international market. Hence, indigenous innovation is of particular importance to fill the void. Although this is a long-term national effort that may not lead to immediate results, sustaining a high level of expenditure on domestic advanced technology research in the future is needed. This policy can be expected to fulfill two strategic goals. One is to strengthen the national ability of basic research for indigenous innovations to achieve independence and self-reliance in future technological development. This will help secure China's international image as an innovative and responsible nation. The second goal is to enhance the overall national capability of internalizing imported technologies for further diffusion and innovation. This function of R&D can never be over-emphasized, as the true benefits of adopting a new technology rely on its step-by-step incorporation into the production process. In addition, policies relating to free market competition and intellectual property protection and their effective enforcement are required. As part of diffusion efforts, government policies should also pay special attention to financial incentives for energy-efficiency investment, energy-efficiency education and training, and demonstration programs (Price et al., 2011).

Closely related to the situation of high energy intensity in China is the nationwide high share of coal consumption, especially in western provinces (Chai et al., 2009; Zhang et al., 2011). Different from other countries, China is a coal-dominated country since it has large quantities of coal reserves, as compared to oil and natural gas. Although the share of coal consumption has decreased in recent years, coal still accounted for 66.6% of total energy consumption in 2012. Facing serious environmental degradation, the Chinese central government has increased the share of clean power, such as natural gas, hydro power, and nuclear power. Specifically, the

share of natural gas in total energy consumption has continuously increased from 2.2% in 2002 to 5.2% in 2012. In order to ensure future supply of natural gas, in 2014 Russia and China concluded a deal to supply 400 billion US dollar worth of natural gas to China over three decades. The share of hydro power increased from 5.9% in 2000 to 7.6% in 2012 and the share of nuclear power from 0.4% in 2000 to 0.8% in 2012. Besides, the development of other new and clean energy, for example, biomass energy, is urgently needed. Looking into the future, it can be expected that the change of energy consumption structure may drastically repaint the energy intensity picture of China.

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Appendix 4.A Rook contiguity spatial weights matrix

The reference spatial weights matrix adopted in this paper is based on the rook rule, in which only the first-order contiguity sharing a length (not a point) of boundary is considered. W is the spatial weights matrix with elements W_{ij} equals to 1 if regions i and j share a common border, 0 otherwise, and $W_{ii}=0$ for all i . Let L_{ij} denote the length of share boundary, between spatial units i and j , then these so-called rook contiguity weights are defined by

$$W_{ij} = \begin{cases} 1, & L_{ij} > 0 \\ 0, & L_{ij} = 0 \end{cases}$$

